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Recommendation System Using Machine Learning: A Review Paper

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Recommendation System software aims at helping users by giving recommendations when faced with big amounts of information. Big information requires time to process and generate a recommendation. It also requires a model of knowledge from a group of data to give the appropriate recommendation. One of the ways to optimise the recommendation system is machine learning. This article discusses recommendation system model development, including the collaborative filtering model, the content-based model, the knowledge based model, the demography model, and a hybrid model using machine learning. This is to increase accuracy and simplify the computational process on the recommendation system.

Key words: *Recommendation system, Machine Learning.*

Introduction

Recommendation system software aims at helping users by giving recommendations when they are faced big amounts of data (Aggarwal, 2017). The given recommendation is expected to help users in deciding things, such as what things to buy, what books to read, or what music to listen to and so on (Aggarwal, 2017).

Nowadays, online vendors equip their systems with the machine of recommendation, and most internet users use the service in daily life. In the system, recommendation refers to the product or the service that is recommended by the system for the users. To produce a list of things that would be recommended for the users, or to predict how many users would like that particular thing, a system is required to analyse the past preferences of other users who share common thoughts or would benefit by descriptive information about the things (Guo, Wang, & Li, 2017).

In the era of Big Data, there is abundant information, which requires time to process or to generate a quick recommendation. A knowledge model from a group of data is needed to provide a proper recommendation. One of the ways to optimise the recommendation system can be achieved by employing machine learning. The term machine learning, basically, means the process of computer learning from data (Felicia et al, 2017).

A lot of algorithms come from the discipline of machine learning, and the sub-discipline of artificial intelligence, which generates algorithms for learning, predicting and making decisions (Fernández-García, Iribarne, Corral, Criado, & Wang, 2019). Some algorithms involving machine learning that are frequently used in the recommendation system are the classification algorithm and clustering.

In this study, we reviewed the model of the recommendation system when combined with algorithm machine learning. We present the literature from various disciplines which benefit by the recommendation system. The contribution of the reviews in this paper is divided into parts:

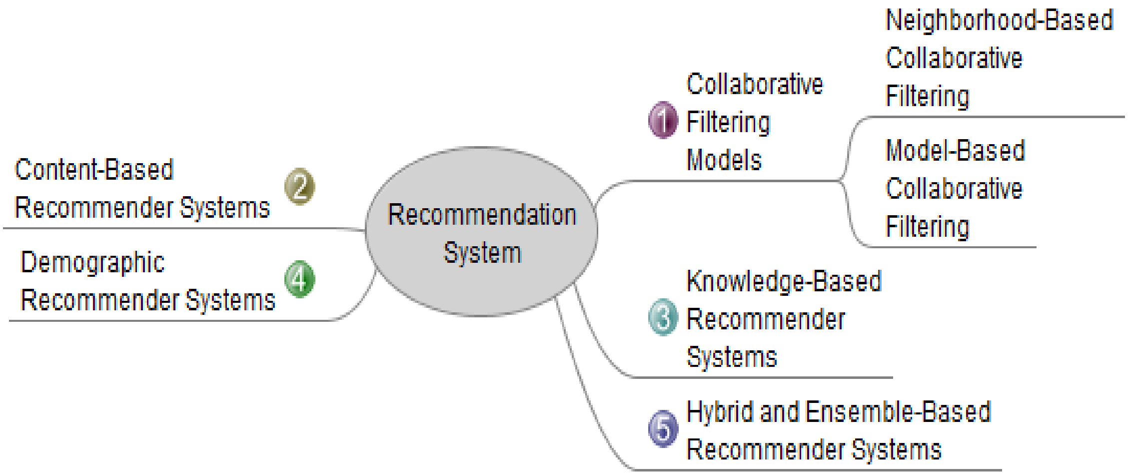
1) The systematic classification from the basic model that existed in the recommendation system;
2) The systematic classification and the analysis of the recommendation system which is combined with machine learning;
3) The taxonomy as the combination of the model of recommendation system and the machine learning.

The motivation to write this research article is to reveal the development of the recommendation system method that is frequently used and the algorithm machine of learning that is used to blend the recommendation system.

Recommendation System

There are a lot of model/method that have been found and developed to provide a reliable recommendation system. The basic recommendation system models are divided into 5: 1) Collaborative Filtering Models (CRFS), 2) Content-Based Recommender System (CBRS), 3) Knowledge-Based Recommender System (KBRS), 4) Demographic Recommender System (DRS) (Elyes & Haj, 2017), and 5) Hybrid and Ensemble-Based Recommender System (Darekar, 2018); (Thiengburanathum, 2018).

Picture 1. Basic Model of Recommendation System



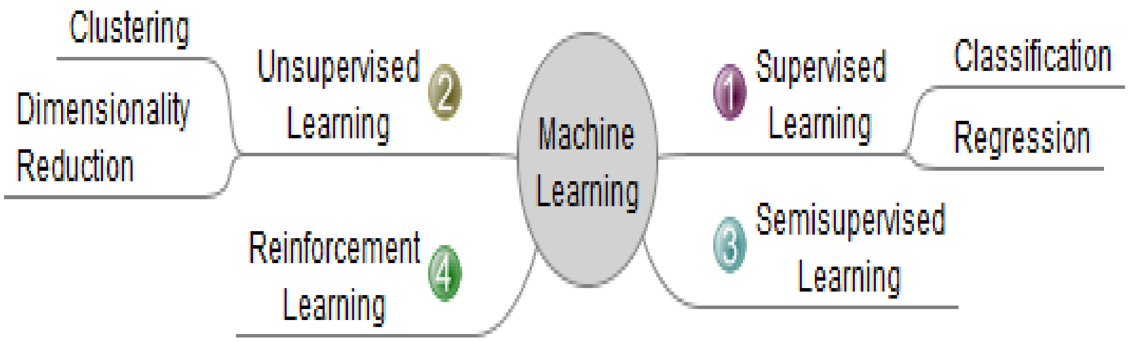
CFRS is divided into two models: User-based and Item-Based Collaborative Filtering. Those models are the most frequently used systems of recommendation (Mohapatra, Swain, & Basa, 2019). The basic idea of CFRS is that the unconsidered level can be counted on since the considered levels are often found to be correlated with various users and items (Alonso, Bobadilla, Ortega, & Moya, 2019).

In CBRS, the profile of the user consists of the item content that would be employed. The description-match of the item-users, furthermore, can be adopted as the recommendation algorithm (Elyes & Haj, 2017). In KBRS, a knowledge-base is constructed from the users requirements and the items' constraints. Recommendation is performed by an inference procedure (Samin & Azim, 2019). DRS is a model which is based on the demographic characterisation of the consumers and recommends the item list which possesses the most positive feedback from the consumers who share an identical demography with the target ones (Hasija, 2017). The combination between two or three of the basic models of the recommendation system is called a Hybrid or Ensemble-Based Recommender System.

Machine Learning

A study (Fernández-García et al., 2019) said that Machine Learning is one of the applications of artificial intelligence which uses the statistical technique to generate an automatic model from a group of data that gives the computer the capability to 'learn'. There are 4 learning categories in machine learning: 1) Supervised Machine Learning Algorithms, 2) Unsupervised Machine Learning Algorithms, 3) Semi-Supervised Machine Learning Algorithms, and 4) Reinforcement Machine Learning Algorithms.

Picture 2. Different type of machine learning



Supervised machine learning is the machine learning algorithm that can apply the existing information on the data by giving a particular label. Supervised learning is divided into two parts: the classification and the regression. The algorithms that are frequently used on the classification of machine learning are Naïve Bayes, kNN, Decision tree, C 4.5, and SVM. The algorithms in the regression are Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and Logistic Regression.

Unsupervised machine learning is the algorithm of machine learning that is used on data which does not have information that can be applied directly (aimless). Unsupervised machine learning is divided into two categories: Clustering and Dimensionality Reduction (Meng & Idris, 2015). The algorithm that is frequently used on the recommendation system on the part of clustering is the K-Means.

Semi-supervised machine learning is the algorithm that is used to conduct learning on labelled and un-labelled data. Reinforcement machine learning is the algorithm which has the ability to interact with the learning process conducted. This algorithm gives points (reward) when the model is getting better, or takes a point (error) when the model is getting worse.

Discussion

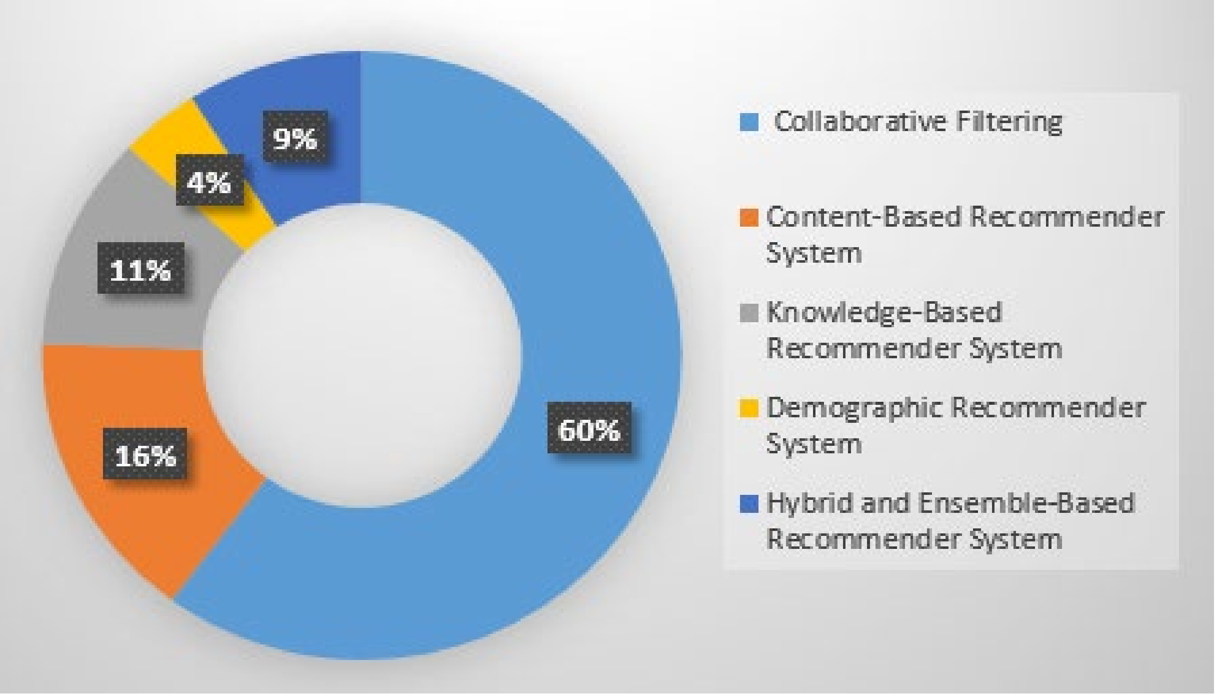
The concept of recommendation system has been frequently and broadly used in almost all areas of business, in which consumers need information to make decisions. The system of recommendation is the model of application from the result of observation towards the condition and expectation of the consumers. This is the reason why the recommendation system requires the proper model of recommendation so that the recommendation made would match with the consumers' expectation, and help them decide on the desired products. The use of recommendation systems nowadays is positively popular in the aspect of commerce, health, news, movie, and tourism. The distribution of basic model can be illustrated in table 1.

Table 1: The Use of Basic Model of Recommendation System

Model of Recommendation System	**Research Paper**
Neighbourhood-Based Collaborative Filtering	Liang & Wang, 2016, Wang Bailing, Huang Junheng, Zhu Dongjie, 2016, Wulam, Wang, Zhang, Sang, & Yang, 2019, Jothilakshmi & Thangaraj, 2018, Qian Wang & Yuan, 2019, Mohapatra et al., 2019, Alonso et al., 2019, Ziani et al., 2017, Nouh, Lee, Lee, & Lee, 2019, Roy, Choudhary, & Jayapradha, 2017, Camacho-navarro et al., 2017, Series, 2019, Jingshuai Zhang, Ouyang, Xie, Rong, & Xiong, 2018, Guo et al., 2017, Wasid & Ali, 2018, Yang, Hsu, Hua, Cheng, & Engineering, 2019, Kaushik, 2018, Tran, Member, & Kim, 2019, W. Zhang, Id, Xu, & Jiang, 2019, Wang, Wang, & Xu, 2018, Thiengburanathum, 2018, Darekar, 2018, Srinivas, Balaji, & Saravanan, 2016, Elyes & Haj, 2017, Ramzan et al., 2019.
Model-Based Collaborative Filtering	Bobadilla, Bojorque, & Hurtado, 2018, Wang et al., 2018, D. Liu, Chen, Chou, & Lee, 2018.
Content-Based Recommender System	Thiengburanathum, 2018, Darekar, 2018, Srinivas et al., 2016, Elyes & Haj, 2017, Fernández-García et al., 2019, Geng, Tan, Niu, Feng, & Chen, 2019.
Knowledge-Based Recommender System	Thiengburanathum, 2018, K. Zhang, Xin, Luo, & Guo, 2017, Palani, Nalla, & Supriya, 2018, Junjie Zhang, Zeng, Koehl, & Dong, 2018, Bafna, Shirwaikar, & Pramod, 2019, Samin & Azim, 2019, Geng et al., 2019.
Demographic	Darekar, 2018, Elyes & Haj, 2017, Hasija, 2017.
Hybrid and Ensemble-Based Recommender System	Darekar, 2018, Thiengburanathum, 2018, Wulam et al., 2019.

Picture 1 reveals that the model of collaborative filtering is frequently used by many researchers in establishing the recommendation system by as much as 60%. The Content-Based Recommender System is the basic model that is also frequently used by the researcher.

Picture 3. The Percentage of the Use of Recommendation System Model



Based on the paper reviews, the most frequent used of the recommendation systems are CFRS and CBRS. These models are easy to implement and add new data. We do not need to consider the content item that is recommended, or the good scale with the co-rated item.

The model of CFRS is frequently used by the researchers due to its superiority. However, there are few weaknesses. Natural scarcity of user-item rating data can be problematic in many domains and settings, limiting the ability to generate accurate predictions and effective recommendations. The collaborative filtering sparse data makes it difficult to: 1) compare elements using memory-based solutions; 2) obtain precise models using model-based solutions; 3) get accurate predictions; and 4) properly cluster elements. CFRS also has limited scale capabilities on the big datasheet and it requires big resources to conduct the computational processes.

Some approaches have been conducted by the researchers to fix the weaknesses of the basic model on recommendation system. One of the approaches is by combining the power of a different model to fix the problems. This combination is called Hybrid. Table 2 indicates the use of the hybrid model.

Table 2: Hybrid Model

<table>
<tr><th>Model 1</th><th>Model 2</th><th>Model 3</th><th>Research Paper</th></tr>
<tr><td rowspan="4">CF</td><td rowspan="3">CB</td><td>-</td><td>Y. Liu, Zhang, Jin, & Yuan, 2019,Srinivas et al., 2016.</td></tr>
<tr><td>KB</td><td>Jorro-aragoneses, Recio-garcía, Díaz-agudo, & Jimenez-díaz, 2019, Thiengburanathum, 2018.</td></tr>
<tr><td>DR</td><td>Darekar, 2018,Elyes & Haj, 2017.</td></tr>
<tr><td>KB</td><td></td><td>Jorro-aragoneses et al., 2019.</td></tr>
<tr><td>CB</td><td>KB</td><td></td><td>Geng et al., 2019.</td></tr>
</table>

The fixing of the basic model of the recommendation system is also conducted by employing algorithms in machine learning. The use of algorithms on machine learning is employed, especially in solving problems on accuracy when working with big data to minimise the existing computational problems. Table 3 indicates the use of algorithm machine learning on the system of recommendation.

Table 3: The Use of Machine Learning Algorithm on Recommendation System

Model Recommendation System	**Machine Learning Algorithm**	**Research Paper**
Collaborative Filtering	Logistic Regression, Matrix Regression	Liang & Wang, 2016,Wang Bailing, Huang Junheng, Zhu Dongjie, 2016.
	C 4.5, Bagging and Boosting Decision Tree	Jothilakshmi & Thangaraj, 2018,Wulam et al., 2019,Camacho-navarro et al., 2017.
	Fuzzy, Hybrid	Yang et al., 2019,Ramzan et al., 2019,D. R. Liu, Chou, Chung, & Liao, 2018.
	Associated item	Guo et al., 2017.
	Restricted Boltzmann Machines (RBM), Vector Space Model (VSM), Support Vector Machine	Jingshuai Zhang et al., 2018,Wang et al., 2018,Ziani et al., 2017,Roy et al., 2017.
	K-Means	Series, 2019,Wasid & Ali, 2018,Kaushik, 2018,Tran et al., 2019.
	Matrix Factorisation	Alonso et al., 2019, W. Zhang et al., 2019, Bobadilla et al., 2018,D. Liu et al., 2018.
	KNN	Qian Wang & Yuan, 2019,Mohapatra et al., 2019,Nouh et al., 2019.
Content-Based Recommender System	ANN, Logistic Regression	Fernández-García et al., 2019.
Knowledge-Based Recommender System	LDA, Naïve Bayes, NN	Samin & Azim, 2019,Palani et al., 2018.
	Association Rule, Cluster	Junjie Zhang et al., 2018,Bafna et al., 2019.
Demographic	Fuzzy Clustering	Hasija, 2017.
Hybrid	DT, SVM, MLP, KNN	Thiengburanathum, 2018,Elyes & Haj, 2017,Srinivas et al., 2016.
	Neural Network	Zhao, 2018.
	kNN	Darekar, 2018,Elyes & Haj, 2017.

With the method of CFRS, there is a problem by which the new item, which does not have a rating, cannot be recommended since the data rating is needed in the process of recommendation. The classification technique is needed to solve this problem. The findings of these studies by Qian, Wang and Yuan (2019), Mohapatra et al. (2019), and Nouh et al. (2019) showed that the algorithm of the nearest neighbour, which is used in CFRS, is the best algorithm to give classification to the objects based on the closest learning data towards the objects. The algorithm of nearest neighbour is also called the lazy learner, and easily keeps or saves the data to memory. It is thus able to classify new items by comparing them with the previous saved items by employing the similarity function. This algorithm is the best approach to find cases by calculating the relationship between new cases with the previous ones by doing the mismatch of some existing features which have similarity. The purpose of this algorithm is to classify the new object based on the attribute and training sample. The Classifier does not use any model to be matched and is only based on memory. The formula to calculate this algorithm is:

$$Similarity(T,S) = \frac{\sum_{i-1}^{n} f(T_i, S_i)' * w_i}{w_i}$$

Description:
T = new case
S = case in memory (saved)
n = number of attributes in every case
i = individual attribute between 1 up to n
f = similarity function of attribute i between case T and case S
w = the given weight to the i attribute

Besides the classification method that is employed to fix the model of CFRS, the method of clustering is frequently used to fix it. The findings of Series (2019) Kaushik (2018), Tran et al. (2019) showed that the weakness of the CFRS model, which is to consider all objects in giving a recommendation, can be reduced by using the algorithm of K-Means. K-Means is the algorithm which categorises objects that would be recommended based on identical users, so that the process of recommendation does not need to consider all objects. Principally, the use of K-Means aims at narrowing the matrix dimension in choosing some similar item rating or users' tendency on liking the same items.

Studies by Alonso et al. (2019), Zhang et al. (2019), Liu et al. (2018) suggested that the use of algorithm matrix factorisation on the model of CFRS, in the level predicting, can generate relatively small errors. The technique of matrix factorisation is one of the most frequently used methods to solve the problem of data and that data's imbalance (Bobadilla et al., 2018). According to the hidden factor model of the matrix factorisation, the method of matrix factorisation will categorise users and items with the vector factor, which is drawn from user rating and the item factors purposed for recommendation. The method of matrix factorisation has the advantage of not involving other information but the rating of the users on items to obtain a rating prediction matrix. This can be considered as the process to gain real data with the linear combination from other hidden factors. However, the matrix is not solid, it would be easily interpreted.

The use of the CF model would be a problem when it is face to face with the online data (Liu et al., 2018). Because the data is online, it changes every time, which demands that the model should be retrained. The model renewal needs a lot of money and time (Zhao, 2018). Network neural suing would solve the problem. The ConvMF model mainly employs CNN to extract latent item features.

CF learning works by finding previous users with the targeted ones by giving recommendations that fit with the users' choices (Darekar, 2018). Content-based learning involves users who possess knowledge regarding the item. The item which has been recommended would be exposed to the target users based on the 'taste' of the previous ones.

The recommended work (Geng et al., 2019) and books (Darekar, 2018) is based on matching the content, preference and profile to increase the accuracy in recommending things. In CBRS, new items are recommended based on their similarity to items already present in the users' profile. An algorithm is used to categorise the identical work field. The similarity of two kinds of work is measured using cosine similarity between their vector space representations:

$$sim(J_a, J_b) = \frac{\sum_{i=1}^{m} w_i^a x\, w_i^b}{\sqrt{\sum_{i=1}^{m} (w_i^a)^2}\, x \sqrt{\sum_{i=1}^{m} \left(w_i^b\right)^2}}$$

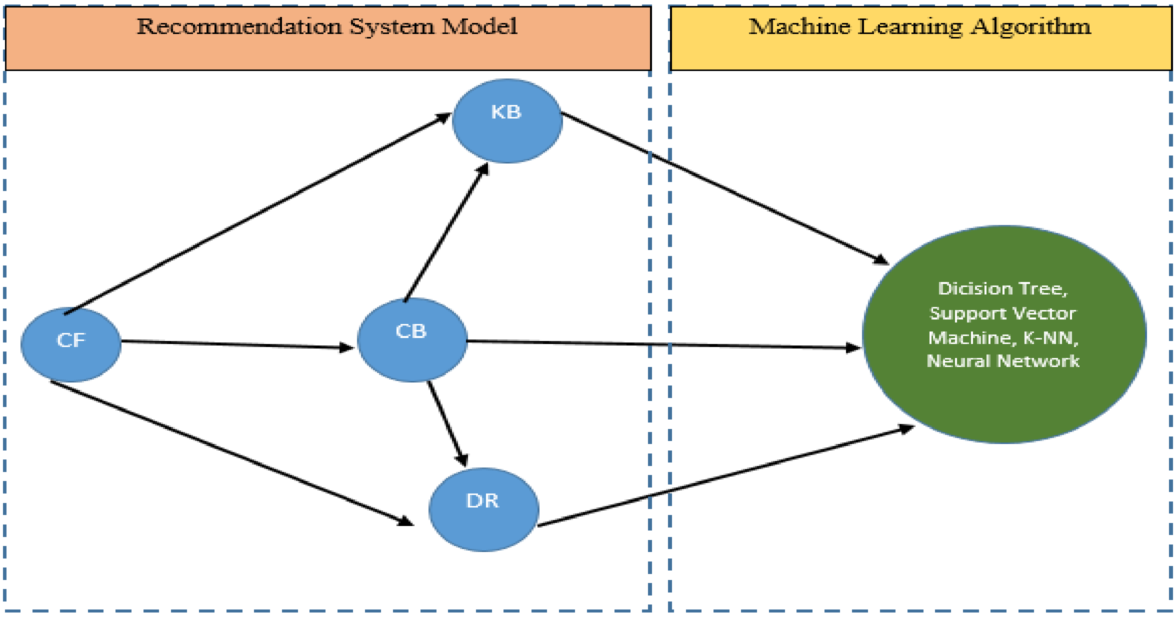
Where w_i^a and w_i^a are the weights of the feature f in job J_a and J_b respectively.

KBRS is a model that employs personalisation rules on the knowledge base. The rules are designed on the basis of the particular priority scales. The priority scale is measured by the prediction on the priority of the need towards particular items. The prediction (Samin & Azim, 2019) (Palani et al., 2018) regarding priority employs one of the algorithms in ML. These are LDA, Naïve Bayes dan NN (Wang et al., 2018).

The system proposes the hybrid in the field of tourism, which already combines the well-known methods, such as: collaborative (CF), Content Based Filter (CB) and demographic filtering (DF) (Elyes & Haj, 2017). To apply this recommendation method, we have applied the different machine learning algorithms, which are the closest neighbour of K (NN) for CB and CF, and the three of decision for DF. The process of hybrid is the best choice to solve the problem of cold start. To increase the accuracy of recommendation, we use two techniques of hybridisation: switching and weighting. The broad experimental study was conducted based on the different evaluation matrix using the extracted data from TripAdvisor. Our result indicates that the hybrid method is more accurate than the other recommendation approaches, which are employed separately.

In the field of tourism, the proposed destination RS is based on demographic. This involves two step filtering features to erase the irrelevant and exaggerating features using the classifier Decision Tree (DT). The DRS offers interpretation, transparency and efficiency for the tourists when they are trying to make decision (Thiengburanathum, 2018). The result of the experiment indicates that our proposed DRS based model performs well and can give personalised recommendations related to the direction of the tour, which are satisfying for the users. From the existing model of the recommendation system, we can connect the fixing of the recommendation system by using algorithm machine learning. Picture 2 reveals the relationship of the development/repair of the recommendation system model.

Picture 4. The Taxonomy of recommendation system model repair



Conclusion

The recommendation system aims at helping users in the process of making decision. Some algorithm system recommendation models include CFRS, CBRS, KBRS, DRS, Hybrid and Ensemble, which are frequently used in e-commerce, health, tourism and other fields. Based on the paper review that has been conducted, the CFRS model is the most frequently used. CFRS is a common recommendation approach that relies on user-item ratings. However, the natural sparsity of user-item rating data can be problematic in many domains and settings, limiting the ability to generate accurate predictions and effective recommendations. This also happens with the model of CBRS, KBRS and DRS, which have weakness in data processing when providing the expected recommendation.

Some of the supervised and unsupervised algorithms in machine learning, such as LDA, Logistic Regression, C4.5, bagging and boosting decision tree, fuzzy, K-Means, matrix factorisation, kNN, SVM dan neural network, are used to overcome the weakness in the basic model of the RS.

Much research conducted in the field of RS by blending machine learning indicates that increasing accuracy and minimising computational time is needed. The use of algorithm network neural can overcome the obstacles of the data which are in real time in the process of model management.

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